INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 06 ISSUE: 11 | NOVEMBER - 2022 IMPACT FACTOR: 7.185 ISSN: 2582-3930

Supplier Selection using Multi Criteria Decision Making (MCDM) Models and Random Forest Algorithm

Sruthi Sreekumar
Department of Computer Science & Engineering
SRMIST, Vadapalani
Chennai, India
ss4297@srmist.edu.in

Neelapa Reddy Sanjana
Department of Computer Science & Engineering
SRMIST, Vadapalani
Chennai, India
nr3413@srmist.edu.in

Shreya Nahar
Department of Computer Science & Engineering
SRMIST, Vadapalani
Chennai, India
sn7692@srmist.edu.in

Mrs. Indumathy M
Department of Computer Science & Engineering
SRMIST, Vadapalani
Chennai, India
indumatm@srmist.edu.in

***Abstract* — Supplier Selection plays a crucial part in Supply Chain Management. The issues with inefficient supplier selection has been an emerging issue in the industry making it necessary for a solution to be discovered. Great academicians and industrialists brought in the concept of Multi-Criteria Decision Making (MCDM) methods for effective supplier selection. These approaches can be used for small scale analysis and selection where the recent performance of the company is used as the criterion for the selection. However, the complexity of such approaches may increase significantly, especially when considering the performance of the suppliers from past few years as the criteria for supplier selection. To address this problem, we have used the Random Forest Algorithm (RF). The applicability of the approach is demonstrated using data from Textile Industry Supplier Performance from the past 5 years. Results show that Random Forest can successfully lead to an effective supplier selection, which would lead to a less complex but efficient application of Supplier Selection.**

Keywords—supplier selection, MCDM, Machine Learning, Random Forest

I. INTRODUCTION

Continuous development of the market of textile services has brought significance to the implementation of modern management methods as one of the crucial elements in the operation of the supply chain. Supply chain management (SCM) oversees how goods and services evolve from the idea creation till implementation to the final product. While specifically talking about the textile industry, it's very important that the materials are the best for the products released, thus making it highly necessary for the production companies to choose the best suppliers.

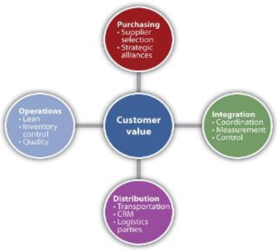

Fig 1.1: Importance of Supplier Selection

As shown in Fig 1.1, Supplier Selection is considered one of the financial factors of the industry “Customer Value”. Supplier selection is a critical process for the overall turnover of the company. The products manufactured after will be by-products of the supplier chosen. In textile industry, the materials and its composition bring about more than half of the total cost and have immense impact on project schedule. Therefore, an efficient concept is needed, as the Supplier Selection which brings out large benefits to the company in terms of quality, time and service.

II. LITERATURE REVIEW

A. *Supplier Selection*

The supplier selection is an important solution when it comes to SCM. Recently the competition in the industry has considerably increased among the suppliers. Hence categorizing the suppliers based on their performance has gained importance. The selection process is crucial for boosting the competitiveness of the business and necessitates the evaluation of many options based on various factors. Supplier selection is one of the most important factors, according to Tookey. A MCDM challenge, it calls for both quantitative and qualitative standards.Another method used when there is vagueness in our personal judgment is the Random Forest, which is a supervised machine learning model that works using the decision trees. Now once we investigate the information we have got, the grading of every provider on every criterion requires a fair amount of choices to be implemented in each level of the problem. So they should have decision trees in each level and a forest of random decision trees to connect all i.e. Random Forest. A suitable supplier selection would grow the customer satisfaction, decrease purchasing costs, decrease product lead time, improve profits and improve the competitiveness.

B. *Supplier Selection process*

Supplier selection involves 2 different types of tools, Qualitative and Qualitative tools. Each of these is a significant tool in the processing of the suppliers based on the criteria. As shown in Fig 2.1, the requirements and the criteria is chosen first which makes the primary step for supplier selection. Then we have Quantitative tools to categorize the suppliers based on the criteria and requirements.

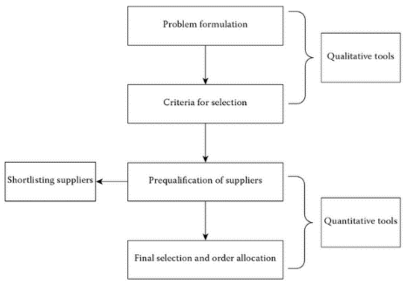

Fig 2.1: Representation of Supplier Selection Process

Supplier Selection Methods

These methods are the three MCDM approaches we will be implementing:

ANALYTIC HIERARCHY PROCESS(AHP)

By comparing its criteria with various alternatives and developing relationships with them, AHP offers a rationalised framework for a necessary use.

TECHNIQUE FOR ORDER OF PREFERENCE BY SIMILARITY TO IDEAL SOLUTION(TOPSIS):

TOPSIS poses as a sensible and helpful technique for ranking and choice of a variety of outwardly determined alternatives through distance measures. It's one of the numerical strategies of the multi-criteria higher cognitive process.

SIMPLE WEIGHTED RANKINGS(SWR):

SWR technique is beneficial for distinguishing a set of candidate suppliers from a probably massive set of accessible suppliers.

RANDOM FOREST ALGORITHM(RF):

In the Random Forest Technique, numerous decision trees are used to represent various sub-criteria of the provided dataset, and this algorithm averages them to improve prediction accuracy [8]. While growing trees, the random forest adds more randomness to the model. Instead than looking for the most significant feature when dividing a node, it looks for the best feature among a random subset of features. As a result, it minimises the variation and solves the overfitting issue in decision trees, increasing accuracy.

III. SYSTEM ARCHITECTURE AND DESIGN

The supplier selection process is performed according to Fig 3.1. The diagram is based on the 3 MCDM approaches that we will be using in this paper. AHP, TOPSIS and SWR are the techniques that will be used for this supplier selection process. The first step is the most important step to the whole process, to note down the criteria based on their needs. The second will be to categorize the criteria based on its relevance to the factors like customer value etc. After selecting the criteria, we need to use all 3 MCDM approaches to find the ranking of the suppliers based on the criteria. To select the ideal supplier, we blend the outcomes from the various MCDM strategies. To choose the best provider in the competitive market, we utilise decision trees in conjunction with the machine learning technique Random Forest to assess the supplier's historical performance in light of the criteria.

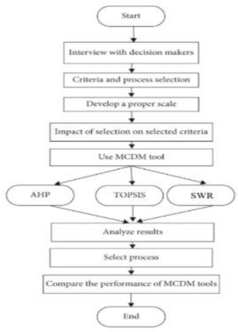

Fig 3.1:Supplier Selection using MCDM

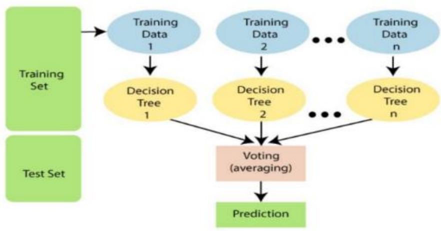

Fig 3.1:Supplier Selection using Random Forest

IV. METHODOLOGY

We propose an MCDM method, starting with AHP in the beginning, followed by TOPSIS and SWR, in order to fill the research gap noted in the literature review in the previous section. We must first prepare the data in accordance with the supplier selection procedures before deciding on the criteria.

A. *Data Preparation*

We have considered a dataset of Textile industry suppliers data. The Table 4.1 contains all the columns of the dataset.

Parameter	Column	Description
Supplier Number	SbjNum	This is the serial number given for each supplier
Quality	QA1 - QA5	Defect & Scrap Ratio, Quality Assurance etc.
Price	PR1-PR4	Cost effective, Consistent prices etc.
Delievery	DE1 - DE5	On - Time Delivery, Quality, Cargo etc.
Service	SE1 - SE5	After sales service, Fleixibility, Reachability etc.

Table 4.1:Columns of the dataset

VOLUME: 06 ISSUE: 11 | NOVEMBER - 2022 IMPACT FACTOR: 7.185 ISSN: 2582-3930

We processed the data collected in the form of a questionnaire

into a combined data based on the criteria required. The basic criterion/factors are Quality, Delivery, Price and Service. Hence, we chose the below 4 criteria based on the research we performed.

- Quality
- Price
- Delivery
- Service

Our next step was to get the weight of each criteria using a trial-and-error generated criteria scoring matrix. This way we can analyze which criteria is most scored and assign weights accordingly.

B. Criteria Scoring

As mentioned above the 4 selected criteria are evaluated based on a scoring matrix. This scoring matrix as shown in Fig 4.1 is created using trial and error method.

```
The criteria score matrix is:
[[1.       4.       3.       7.      ]
 [0.25     1.       0.33333  3.      ]
 [0.33333  3.       1.       5.      ]
 [0.142857 0.33333  0.2      1.      ]]
```

Fig 4.1: Scoring Matrix

Using this matrix we perform an evaluation to rank the criteria based on their scores or in other words criteria weights. These criteria weights as shown in Fig 4.2 are going to be used in the rest of the approaches for supplier selection.

```
The priority for Quality is: 0.5396442239788989 .
The priority for Delivery is: 0.13146416409903217 .
The priority for Price is: 0.2715476119000481 .
The priority for Service is: 0.057344000022020794 .
```

Fig 4.2: Criteria Scoring

According to Fig 4.2, the criteria Quality is weighted the most followed by Price the second highest, then the Delivery followed by Service with almost similar weights.

C. MCDM approaches for Supplier Selection

4.1. AHP - Analytic Hierarchy Process

AHP may be a widely used MCDM approach for choice processes. This technique is used for ranking a collection of alternatives in an exceedingly set of alternatives. The selection is completed with regard to overall goal, that is counteracted into a collection of criteria as shown in Fig 4.1.1.

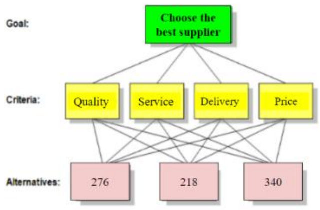

Fig 4.1.1: AHP Process

Every level of the hierarchy contains a numerical priority, allowing for rare and diverse incommensurable items to be compared to at least one another using a logical and consistent method. This ability has aided in setting AHP apart from competing decision-making methods. We have selected four criteria for our article, and since they are all supported by scores from the previous section, we have ranked them as given in Table 4.1.1.

Alternatives, the Suppliers as shown in Fig 4.1.1 are then evaluated exploiting these criterion weights and ranking. The weights measured are allotted to support the AHP basic scale for pairwise comparisons as shown in Fig 4.1.2.

Criteria	Quality	Price	Delivery	Service
Weightage	0.5	0.3	0.13	0.05
Rank	1	2	3	4
Sub - Categories	QA1 - QA5	PR1-PR4	DE1 - DE5	SE1 - SE5

Table 4.1.1: Criteria Ranking based on Scores

The Fundamental Scale for Pairwise Comparisons		
Intensity of Importance	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment moderately favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another; its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
Intensities of 2, 4, 6, and 8 can be used to express intermediate values. Intensities of 1.1, 1.2, 1.3, etc. can be used for elements that are very close in importance.		

Fig 4.1.2: AHP Fundamental Score

4.2. SWR - Simple Weighted Ratings

This technique is useful for identifying a subset of candidate suppliers from a potentially large set of available suppliers. The difficulty is when we have numerous criterias for the selection of the suppliers. For example, if provided 2 criterias with equal weights for supplier selection. SWR uses the same criteria ranking and weights as provided in the AHP for its implementation making it a subset of AHP.

The methods we consider in this paper allow us to consider both qualitative and quantitative criteria. Qualitative criteria are considered by assigning a value that ranks each supplier on the qualitative dimension and weighting these values to compute a weighted score for each supplier. We will consider two variants of such a weighted method. The first method sums the weighted scores for the various attributes and the second computes the product of the attribute scores raised to the power specified by the weight as shown below :

The Weighted Sum Method (WSM)

$$V(a) = \sum_{i} w_i v_i(a)$$

The Weighted Product Model (WPM)

$$R(a,b) = \prod_{i \in I} \left({v_i(a)}/{v_i(b)} \right)^{w_i}$$

Fig 4.2.1: SWR Calculation

4.3. TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution

Using this method, you can choose the solutions that are both the most like the perfect solution and the furthest away from it. TOPSIS bases its model on the premise that the criteria either rise or fall with time. In multi-criteria situations, the criteria are frequently the wrong dimensions, hence normalisation is required. This technique also makes use of AHP's continuous criteria ranking and weights. Fig. 4.3.1 displays the process used to analyse the TOPSIS score.

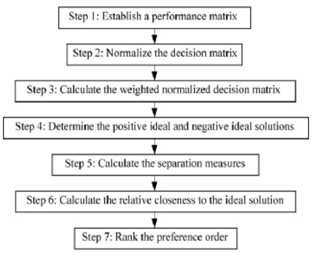

Fig 4.3.1: Methodology

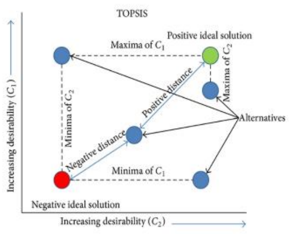

Fig 4.3.2: Graph

The graph in Fig. 4.3.2 makes it obvious how TOPSIS is assessed using both the positive and negative ideal solutions. While TOPSIS determines the optimal solutions and ranks the suppliers according to how closely they are to the ideal solution, the AHP is used to assign weights and rank the alternatives.

4.4. Supplier Selection Ranking based on the MCDM approaches (AHP, SWR and TOPSIS)

Through qualitative comparisons, the AHP is used to specify the weights of each criterion and sub-criterion. The acquisition decisions are then evaluated using TOPSIS. Making strategic and complicated decisions is assisted by this analysis in a thorough and scientific manner. The weighted add model (WSM), which produces the calculation of global priority for alternatives from the additive aggregation of native preferences and criteria weights, is typically used in AHP to determine the preference Pi of alternative Ai. The weighted product model (WPM) in my online code AHP-OS allows users to aggregate alternatives using the product instead of the sum (Goepel 2018). As all the three MCDM approaches are interconnected we have a tendency to integrate all the scores of the three approaches then rank the suppliers that supported the factors. We integrate and build them into proportions with one as maximum and zero as minimum. 1 is that the best resolution and zero is the least suggested resolution.

D. Supplier Selection Ranking based on Random Forest

The data used for the random forest algorithm consists of the 5 years rating of 16 Suppliers in various criteria. Table 4.2 shows the data considered for the evaluation of best suppliers using Random forest. These 16 suppliers were chosen from the first 8 and last 8 performers in the MCDM rating.

Alt/Criteria	89	89	89	89	89	133	133	133	133	133	Rank
Year	2001	2010	2015	2020	2022	2001	2010	2015	2020	2022	0
QA1	0	0	0	0	0	0	0	0	0	0	9
QA2	4	4	4	4	4	0	0	0	0	0	9
QA3	0	0	0	0	0	0	0	0	0	0	9
QA4	0	0	0	0	0	1	1	1	1	1	9
QA5	3	3	3	3	3	0	0	0	0	0	9
DE1	3	3	3	3	3	1	1	1	1	1	6
DE2	0	0	0	0	0	0	0	0	0	0	6
DE3	0	0	0	0	0	0	0	0	0	0	6
DE4	0	0	0	0	0	0	0	0	0	0	6
DE5	0	0	0	0	0	0	0	0	0	0	6
PR1	2	2	2	2	2	2	2	2	2	2	5
PR2	2	2	2	2	2	2	2	2	2	2	5
PR3	2	2	2	2	2	2	2	2	2	2	5
PR4	1	1	1	1	1	1	1	1	1	1	5
SE1	1	1	1	1	1	1	1	1	1	1	5
SE2	1	1	1	1	1	1	1	1	1	1	7
SE3	1	1	1	1	1	1	1	1	1	1	7
SE4	1	1	1	1	1	1	1	1	1	1	7
SE5	1	1	1	1	1	1	1	1	1	1	7

Table 4.2: First and Last 8 Performers in MCDM RATING

Now what it contributes to our paper is that we have got completely different criteria and every criteria would provide different vendors because the best supported its decision tree. Currently with the assistance of Random Forest algorithmic rule we will get to the most effective provider out of the whole selections made. Moreover, to extend the accuracy of the results we can divide the dataset into coaching sets and testing sets for calculation functions. Then the output is given supported Rejection Scores and therefore the suppliers are hierarchically supported lowest to the highest Rejection Scores.

E. The Best Supplier Selection

An optimal solution is achieved only after repeated evaluation with various techniques. Here we have implemented it using 3 MCDM approaches - AHP, TOPSIS and SWR and Random Forest. We used the Random Forest technique to process numerous data at the same time. We combine the proportions derived from the MCDM approaches and the Machine Learning technique to provide the best supplier for the given requirements and criteria.

V. ANALYSIS AND FINDINGS

We are using Python for this Machine Learning process as it is an easy, cheap, robust and adaptable environment. To access such numerous packages, which might facilitate us. with our program we want a GUI (Graphic User Interface). Here we use Google Colab as it has lots of packages which could be used for Machine Learning and moreover it provides various libraries and channels without using command-line commands. We use the regular libraries like:

- Pandas - for data processing and preparation
- Numpy - for using sum, count and arr commands
- Seaborn - to visualize the graphs

We used many other functions like counter, interact, sklearn etc.

The MCDM approaches were evaluated using Evaluation Matrices which were developed using the criteria weights and ranking based on the MCDM approach. These matrices were in later stages used for compiling and forming the scores for each MCDM process.

Random Forest Classifier uses feature choice techniques to represent the suppliers on the basis of their scores. The sampling of rows is performed at the tree level. Thus each tree gets a unique collection of data points. It uses the thought of Rejection Scores to judge the most effective suppliers.

A. *MCDM approaches*

All the 3 MCDM approaches are performed using the same criteria ranking and criteria weights evaluated using the Fig 4.1.2. The criterion and weights considered are shown in Fig 5.1.

```
criteria = ['Quality',
            'Delivery',
            'Service',
            'Price']

criteria_weights = np.array([9,6,7,5])
```

Fig 5.1: Criteria Weights

AHP(Analytic Hierarchy Process): The evaluation of the criteria and their weights is followed by the ranking of the suppliers and alternatives according to their AHP scores. The best provider for the criterion is supplier number 20, followed by 133 and 276 in Table 5.1's findings.

Rank	Supplier Number	AHP Score
1	20	0.95
2	133	0.93
3	276	0.92

Table 5.1: Supplier Selection based on AHP score

SWR(Simple Weighted Rating): By using the same criteria ranking and weights as in Fig 5.1, the results of the SWR have 2 parts. There is Simple Weighted Sum and Simple Weighted Product for which the explanation was given earlier in “SWR” under Methodology.

Rank	Supplier Number	Weighted Sum Score	Weighted Product Score
1	20	4.86	4.85
2	276	4.81	4.80
3	19	4.77	4.74

Table 5.2: Supplier Selection based on SWR score

As shown in Table 5.2, the ranking of the supplier based on weighted sum and product is the following. The result changes slightly when we evaluate based on the AHP and SWR proportion as shown in the graphs Fig 5.2 and Fig 5.3 below. The figure indicates that the first 3 ranks are varying now. The first rank is 20 but it's followed by 133 and 276.

TOPSIS(Technique for Order of Preference by Similarity to Ideal Solution): This depends on the positive and negative idea solution with distancing vectors to determine the best solution through closeness as shown in Fig 5.4. It is further explained in “TOPSIS” under Methodology.

```
#Step 4
PIS = np.max(weighted_matrix, axis=0)
NIS = np.min(weighted_matrix, axis=0)

#Step 5
intermediate = (weighted_matrix - PIS)**2
Dev_Best = np.sqrt(intermediate.sum(axis = 1))

intermediate = (weighted_matrix - NIS)**2
Dev_Worst = np.sqrt(intermediate.sum(axis = 1))

#Step 6
Closeness = Dev_Worst/(Dev_Best+Dev_Worst)
```

Fig 5.4: Best solution through closeness

After getting the TOPSIS score by following the steps above, we then evaluate into proportions. The result of the TOPSIS score based supplier ranking is given in Table 5.3.

Rank	Supplier Number	TOPSIS Score
1	20	0.95
2	276	0.91
3	133	0.89

Table 5.3: Supplier Selection based on TOPSIS score

Final Best Supplier Ranking using MCDM approaches:
It is observed that the AHP gives the most optimal solution because of its hierarchical methodology. SWR also helps narrow down the process by evaluating the Sum and Product Scores to eliminate a few suppliers. Using the closeness factor and ideal solution techniques, TOPSIS also is an equivalent to AHP but AHP holds more advantage because of its flexibility and other factors.

By the end of all the MCDM approaches, the ranking stands as Table 5.4 and the ranking is done based on the proportions evaluated using all the scores of the MCDM approaches.

Supplier	WS Proportion	WP Proportion	TOPSIS Proportion	AHP Proportion
20	1.00	1.00	1.00	1.00
133	1.00	1.00	1.00	1.00
276	1.00	1.00	1.00	1.00
176	1.00	1.00	1.00	1.00
298	1.00	1.00	1.00	1.00

Table 5.4: Final Ranking based on MCDM

B. Random Forest Algorithm(RF)

We have several decision trees on various sub-criteria of the given dataset in this Random Forest Algorithm, and as we know, a forest is made up of trees. This algorithm averages these decision trees to improve prediction accuracy [8]. While growing the trees, the random forest adds additional randomization to the model. Instead of looking for the most crucial characteristic when splitting the node, it picks the best feature from a random subset of it. As a result, it offers a workable solution by lessening the overfitting issue with decision trees and increasing precision. According to the findings of this Random Forest Algorithm, shown in Fig. 5.5, Supplier Number 20 continues to be the best supplier for the buyer's requirements. When compared to the supplier's prior performances, however, Supplier 276 is the second-best instead of Supplier 133. In this model, we have used the Rejection Score and hence the Supplier with the least Rejection Score is the highest recommended supplier as shown diagrammatically in Fig 5.6.

20	0.029129
276	0.036875
176	0.040893
298	0.043080
11	0.043750
4	0.044687
133	0.045162
7	0.049454
89	0.049792
2	0.060349
1	0.063789
19	0.070000
15	0.077485
12	0.083958
3	0.102859
6	0.158736

Fig 5.5: Results using RF

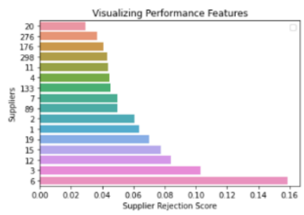

Fig 5.6: Visualizing RF results

VI. DISCUSSIONS AND CONCLUSIONS

From Figure 5.1, 5.2 and 5.3 it can be found out that supplier 20, 133, 276, 176 and 298 have the maximum proportion value thereby ranked highest for the selected criteria ranking and weightage. We could therefore consider them as best options and reject the supplier 46 as it comes at the bottom with the minimum proportion value. According to the Random Forest Algorithm, the top 5 best suppliers list changes. From Figure 5.5 and 5.6 we can see that Supplier 133 is no more in the top 5 because of its past records and performances but Supplier 20 still remains at the top with the lowest rejection score. Since we have used selected data for the Random Forest Classifier, we can also conclude that Supplier 6 is the worst case in the dataset provided.

A. Theoretical And Managerial implications

As we are using a machine learning technique to classify and analyze it, we have saved much of our time and cost involved in the calculation. By using Random Forest Algorithm we can be able to achieve an accurate result of the best supplier using the past 5 years performance of the suppliers. Thus, we conclude that the Supplier Selection is done using 3 MCDM approaches and Random Forest algorithm giving it an advantage over the existing techniques because of the ability to produce accurate results for complex and multiple criteria dataset.

B. Future Research Directions and Limitations

In everything we do no matter how hard we try there are always two sides to a coin i.e we will have both positives and negatives. There are few limitations like, In order to conduct the research, we only focused on large provinces and conducted a qualitative study instead of expanding the sample and conducting a qualitative research with the managers of textile organizations (that would be more beneficial). Doing this would be more valuable if the sample was expanded. Therefore the study still has several limitations that merit further investigation. To conclude that, Supplier Selection has a major impact on the Customer Value Sector of the SCM. Hence many industries use techniques and methods to find the best supplier according to their needs. The best supplier is chosen on the basis of various factors/criterias which majorly depends on the buyer's requirement and criteria and the ongoing market trends. This is where MCDM plays a role since we need to analyze multiple criterias before selecting the best supplier.

The MCDM technique is an old technique and has various methods. These techniques are known to give preference to the stakeholders. Hence the datasets used for the MCDM approach consists of exploratory data of the ratings given by the customers in various criteria. The chosen 3 techniques for this paper, AHP, TOPSIS and SWR complement each other and therefore combined together gives an output based on the comparison made by the three techniques. But the disadvantage here is that we are unable to measure the stability of the supplier and guarantee its performance in the future according to the present data. Here is where we have an advantage of the Machine Learning Techniques.

The Machine learning technique allows us to analyze the data of the supplier’s performance from the past 5 years. Random forest, the technique used for this project allows the buyer to analyze and understand if a company is eligible or not to become the best supplier according to their requirements using their past performances. This makes it much reassuring and promising for the buyer about the stability of their performance now and in future.

There are more MCDM techniques and machine learning algorithms that we can still explore but we have chosen these as they are interconnected in their method of implementation and the results. We can still explore the other approaches to check out for better results and accuracy in the future .We hope that our work will not be limited to literature survey but also provide decision makers with information that will give them greater control over supply chain.

VII. REFERENCES

[1] P. Kaur and N. C. Mahanti, (2008), “A fuzzy anp-Based approach for selecting erp vendors,” Int. J. Soft Comput., vol. 3, no. 1, pp. 24–32.

[2] V. F. Rodriguez-Galiano, B. Ghimire, J. Rogan, M. Chica-Olmo, and J. Rigol-Sanchez, (2012), “An assessment of the effectiveness of a random

forest classifier for land-cover classification," ISPRS J. Photogramm. Remote Sens., vol. 67, no. 1, pp. 93–104.

[3] A. Karami and Z. Guo, (2012), "A fuzzy logic multi-criteria decision framework for selecting IT service providers," Proc. Annu. Hawaii Int. Conf. Syst. Sci., pp. 1118–1127

[4] V. Y. Kulkarni and P. K. Sinha, (2012), "Pruning of random forest classifiers: A survey and future directions," Proc. - 2012 Int. Conf. Data Sci. Eng. ICDSE 2012, pp. 64–68.

[5] B. Heung, C. E. Bulmer, and M. G. Schmidt, (2014),"Predictive soil parent material mapping at a regional-scale: A Random Forest approach," Geoderma, vol. 214–215, pp. 141–154.

[6] M. R. Segal, (2004), "Machine learning benchmarks and random forest regression. Center for Bioinformatics and Molecular Biostatistics, UC San Francisco, USA.,"

[7] P. Parthiban, H. Abdul Zubar, and P. Katakar, (2013), "Vendor selection problem: A multi-criteria approach based on strategic decisions," Int. J. Prod. Res., vol. 51, no. 5, pp. 1535–1548.

[8] J. Ali, R. Khan, N. Ahmad, and I. Maqsood, (2012), "Random Forests and Decision Trees," Int. J. Comput. Sci. Issues, vol. 9, no. 5, pp. 272–278

[9] E. Vasina, Analyzing the process of supplier selection. The application of AHP Method, in Degree Programme in Industrial Management 2014, Centria University of Applied Sciences

[10] M. Zeydan, C. Çolpan, and C. Çobanoğlu, (2011) "A combined methodology for supplier selection and performance evaluation," Expert Syst. Appl., vol. 38, no. 3, pp. 2741–2751.

[11] S. H. Ha and R. Krishnan, (2008) "A hybrid approach to supplier selection for the maintenance of a competitive supply chain," Expert Syst. Appl., vol. 34, no. 2, pp. 1303– 1311.

[12] E.A. Frej, L.R.P. Roselli, J. Araújo de Almeida, A. Teixeira de Almeida, A Multicriteria Decision Model for Supplier Selection in Food Industry Based on FITradeoff Method. Center for Decision Systems and Information Development (CDSID), 19 October 2017.

[13] L. Benyoucef, H. Ding, X. Xie, Supplier Selection Problem: Selection Criteria and Methods, in INRIA. 2003.

[14] E.A. Smirnova, Supply Chain Management St. Petersburg State University of Economics and Finance 2009. M. H. Hugos, Essentials of supply chain management 2011. 62.

[15] C. Cristea, M. Cristea, A multi-criteria decision making approach for supplier selection in the flexible packaging industry. EDP Sciences,

[16] D. Santin, "On the approximation of production functions: a comparison of artificial neural networks frontiers and efficiency techniques," Applied Economics Letters, vol. 15, no. 8, pp. 597–600, 2008.

[17] A.E. Cengiza, O.A., I. Ozdemirb, H. Kusanb, A. Cabuka, A Multi-Criteria Decision Model for Construction Material Supplier Selection. 2017: p. 294 – 301.